Fuzzy Similarity of Facial Expressions of Embodied Agents

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Abstract. In this paper we propose an algorithm based on fuzzy similarity which models the concept of resemblance between facial expressions of an Embodied Conversational Agent (ECA). The algorithm measures the degree of visual resemblance between any two facial expressions. We also present an evaluation study in which we compared the users' perception of similarity of facial expressions. Finally we describe an application of this algorithm to generate complex facial expressions of an ECA.

Keywords: Embodied Conversational Agents, facial expressions, fuzzy similarity.

1 Introduction

The mystery of the human face inspired artists and psychologists for centuries. Recently it has become also an object of interest of computer scientists. Embodied conversational agents (ECAs) – programs that focus on multimodal communication between humans and machines – display facial expressions to communicate. In this paper we focus on modelling the concept of similarity between any two facial expressions of emotion of an ECA. Despite facial expressions are complex objects it is quite natural and easy for human beings to decide if any two facial expressions are similar or not. Our aim is to build an algorithm that simulates this human's skill.

Establishing the degree of similarity between facial expressions can be very useful for an ECA designer. Often the knowledge about facial expressions is restricted only to some particular cases. Despite the evidence that many facial expressions exist [13,15,19] most of researchers (e.g. [3,10,11]) limit their research only to six of them, namely: anger, disgust, fear, joy, sadness, and surprise. Other facial expressions were rarely studied, and as consequence they are difficult to model. We used the algorithm presented in this paper to model different types of facial expressions like fake or inhibited expressions for the expressions like embarrassment, disappointment or contempt (see section 5).

Generally, similarity is very difficult to measure. It is a quantity that reflects the strength of relationship between two objects. The similarity between two objects is measured by comparing their attributes. Two cars are similar if both have the same number of doors, are about 4 meters long, and both are red.

C. Pelachaud et al. (Eds.): IVA 2007, LNAI 4722, pp. 86–98, 2007.

Traditionally the similarity between, two objects is expressed through a *distance function*. In this geometrical tradition two objects are similar if the distance between them is small [25]. On the other hand, *fuzzy similarity* [5] is used to work with objects characterised by loose description. Each object or feature that does not have a precise definition can be described by a fuzzy set. Fuzzy similarity allows for the comparison of any two fuzzy sets. It takes into consideration the various features of objects that characterise them at least partly. Various measures have been proposed to compare any two fuzzy sets [5].

For the purpose of comparing computer generated facial expressions we decided to use fuzzy similarity. It allows us to define attributes of an object by fuzzy sets instead of using precise values. On the other hand, according to many researchers (e.g. [10,16]) each "distinct and labelled expression of emotion" like "expression of anger" or "expression of contempt" is rather a "class" or a "set" of different but similar configurations of facial muscles actions (or a set of different *facial displays*). Indeed, there is not one precise smile or a frown. Each smile is a little bit different but "all smiles" have some characteristics in common. The boundary between smiling and not smiling is also imprecise. Different facial displays of different intensities are classified as smiles. Indeed, in many experiments (e.g. [2,11]) different facial displays involving the same group of muscle contractions were described by subjects with the same label, so an expression of an emotion e.g. "expression of anger" is not a precise concept. It has an imprecise "fuzzy" definition (see also [26]). On the other hand, all facial displays that belong to one category like "happiness", "anger", or "embarrassment" have some common features. Therefore, any category can be defined by a set of fuzzy sets that corresponds to these features.

Our approach follows the results from the psychological theory and experiments. It is based on the *discrete-emotion approach* represented among others by Paul Ekman [7,10]. According to this theory there is only a discrete number of expressions that can be universally recognized by humans. Ekman focuses his research on the six facial expressions mentioned above. We decided not to restrict ourselves to this small set. Thus our algorithm of similarity should work properly with any facial expression as, for example, those described in [13,18,19].

Thus we aim at building an algorithm that:

- is coherent with the discrete-emotion approach and with the results of the experiments about the perception of facial expressions,
- works for any facial expression,
- preserves the fuzziness of the concept of facial expression,
- preserves the different degrees of similarity between facial expressions.

The remaining part of this paper is structured as follows. In next section we present some theoretical aspects of comparing facial expressions. In section 3 we present our algorithm and in section 4 the evaluation study. The section 5 is entirely dedicated to the applications of our algorithm. Finally conclusion and future work are presented is section 6.

2 Fuzzy Similarity

Fuzzy similarity offers a set of methods to compare two objects. As opposed to distance-based similarity, each feature of an object is represented by a fuzzy set. Two fuzzy sets can be compared using *M-measure of comparison* [5]. It expresses the strength of the relationship between the features of two objects. There are different types of the M-measures of comparison. For our application we chose the M-measure of resemblance [5]. It is used for comparing objects of the same level of generality. Using this M-measure it is possible to check whether two objects “have many characteristics in common” [5]. It is often used in case-based reasoning systems. Each M-measure of resemblance S has also two other properties:

- reflexivity: $S(A, A) = 1$,
- symmetry: $S(A, B) = S(B, A)$.

These properties characterise also the process of comparing facial expressions. First of all, comparing facial expressions means to compare objects of the same level of generality. Following Ekman’s theory [10] all expressions are equi-important and distinct. Moreover, in [20] it was found that the perception of similarity between unlabelled facial expressions is symmetrical, i.e. expression A is similar to expression B to the same degree as B is similar to A [20].

In [5] different M-measures of resemblance are proposed. For our application we chose the measure of resemblance S defined by:

$$S(A, B) = \frac{(M(A \cap B))}{(M(A \cup B))} \tag{1}$$

where A and B are two fuzzy sets (μ_A is membership function of A) and M is the fuzzy measure on Ω:

$$M(A) = \int_{\Omega} \mu_A(x)dx \tag{2}$$

This choice was made mainly because of practical consequences. This concrete measure is easy to implement and the process of computation is relatively simple. As a result we obtain the value of comparison $x_i \in [0,1]$ for each pair of attributes. Following the approach proposed in [23] we use *Ordered Weighted Averaging* (OWA) operator to aggregate all values $x_1,...,x_n$. The OWA, $h_W : [0, 1]^n \to [0, 1]$, is defined as:

$$h_W = \sum_{i=1}^{n} w_i b_i \tag{3}$$

where b_i be i-th biggest value between $x_1,...,x_n$ and $W = \{w_1, ..., w_n\}$ is a set of weights with $w_i \in [0, 1]$ and such that $\sum_{i=1}^{n} w_i = 1$ [23]. Finally, we use trapezoid fuzzy sets in order to describe the features of facial expressions as shown in Figure 1. This shape renders the experimental results about perception of facial expressions [2,27]. On the other hand, it is characterised by computational facility.

3 Similarity of Facial Expressions in an Embodied Conversational Agent

In order to implement and test our algorithm we used an existing ECA architecture called Greta [4]. Facial expressions of Greta are described in terms of facial animation parameters (FAPs) [21]. Originally Greta did not offer fuzzy definitions of facial expressions. The static expressions used by Greta needed to be fuzzified. For each FAP of each expression we have defined the fuzzy set of plausible values. First, we have established for each facial feature (i.e. single FAP) the amplitude of values that preserves the reliability and plausibility of a particular movement. It means that for any feature we have established the minimum x_1 and the maximum x_2 plausible values for any expression. Beyond this range the movement is perceived as unnatural. Each fuzzy set FAP$_k$ of a particular facial expression depends on this amplitude of plausible values. We have established that membership is a symmetrical trapezoid with the centre in the point v, where v is a value of the original expression (see Figure 1). The dimensions of the trapezoid depend on the absolute value of the difference: $|x_2 - x_1|$. Using fuzzy definitions of facial expressions we count the value of similarity between them. For that purpose we use the procedure described in the previous section. Let FS(Exp(E$_i$),Exp(E$_j$)) be the value of similarity between two expressions Exp(E$_i$) and Exp(E$_j$). For each FAP$_k$ of Exp(E$_i$) and Exp(E$_j$) we have:

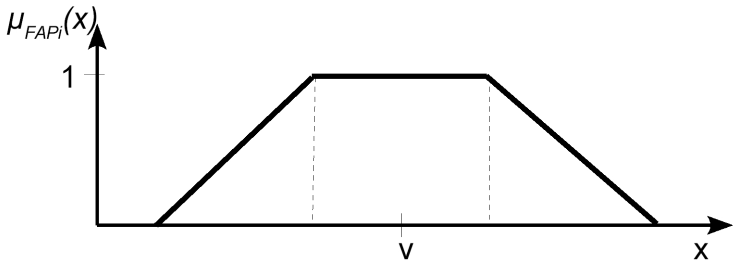

Fig. 1. A fuzzy set of FAP$_i$

$$fs_k = \frac{M(FAP_k(E_i) \cap FAP_k(E_j))}{M(FAP_k(E_i) \cup FAP_k(E_j))} \tag{4}$$

where k = *1,...,n*. Then:

$$FS(Exp(E_i), Exp(E_j)) = h_w(fs_1, ..., fs_n) \tag{5}$$

where h$_w$ is OWA operator with the weights $w_k = \frac{1}{n}$ (see section 2).

Recapitulating, our algorithm works as follow: let E$_u$ and E$_w$ be two emotions whose expressions we want to compare. Thus we want to establish fuzzy similarity between two static expressions: Exp(E$_w$) and Exp(E$_u$). Each Exp(E$_i$) is associated with a number of fuzzy sets such that all plausible *facial displays*

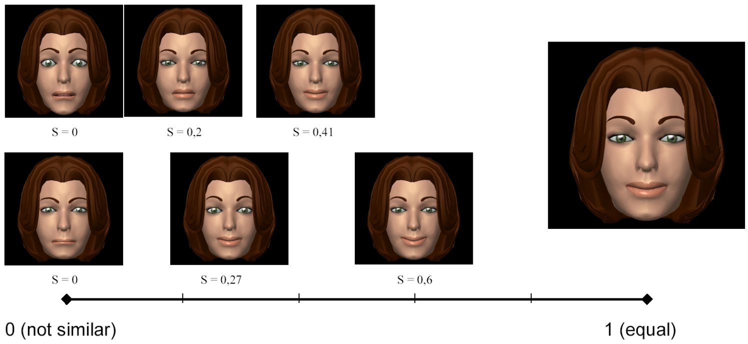

Fig. 2. Fuzzy similarity of facial expressions of Greta agent

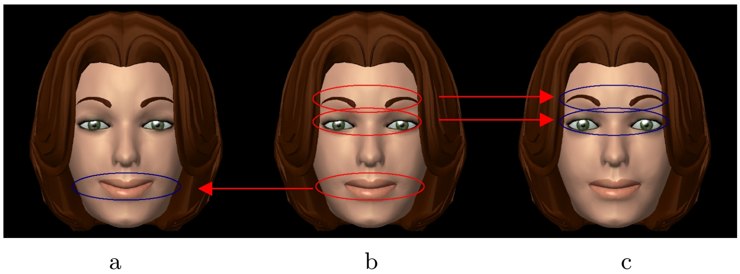

Fig. 3. The example of comparing facial expressions

(in the sense of muscle contractions) for the emotion E_i are defined. That is, for each parameter k of an expression of E_i there is a fuzzy set FAP_k that specifies its range of plausible values. Then the value of fuzzy similarity for each parameter of $Exp(E_w)$ and $Exp(E_u)$ is established. The M-measure of resemblance S is used to find these similarity values. Finally, in the third step, all values are combined by means of the aggregation operator h_w (3).

Let us compare the three facial expressions shown in Figure 3. The values of similarity between them are: S(A,B) = 0.6 and S(B,C) = 0.4. That is, the expression A is more similar to B than C is to B. In Figure 3a, the lips are extended with greater intensity than in Figure 3b. When comparing Figure 3b and Figure 3c, the eye aperture in Figure 3b is more closed than in Figure 3c. Moreover, in these two images, the eyebrows have different shapes. This explains why the similarity between B and C is less than between A and B. The areas of the facial expressions that vary among the three images are marked by a circle.

4 Evaluation

We have conducted an evaluation study to check if our algorithm models adequately the concept of the resemblance of static computer generated facial

expressions. We are unaware of any similar experiment made on computer generated expressions of emotions. Previous evaluation studies of embodied agents ([2,6,17]) mainly analysed the perception of emotions from the computer generated facial expressions. Instead we focus on the process of comparison of any two facial expressions (i.e. the perception of the common features and the differences between them). We avoid considering the problem of interpretation of these facial expressions.

Our main aim is to verify if the values of the similarity established by our algorithm are consistent with human perception of the resemblance between facial expressions. Our hypothesis was that values of fuzzy similarity are proportional to those found by human's perception. In particular, we expected to find that our algorithm and human perception are concordant not only in evaluating if any two expressions are similar to each other or not, but also that different degrees of resemblance perceived are adequately modelled in our algorithm.

4.1 Objects of Comparison

Our objects of comparison are images the emotional facial expressions of the Greta agent. Each image depicting facial expressions follows the same setting:

- each image presents one facial expression of Greta,
- only the face is visible in the image,
- the face is directed at the observer,
- a black background was used.

Each image was saved in jpeg format. An example of the image is presented in Figure 4. In the experiment we used 22 different facial expressions. Each expression is defined by a different combination of FAP parameters and by their values. The expressions are created according to the descriptions presented in the literature. Among others, we used all six facial expressions proposed by Ekman as *universally recognized expressions* of emotions [7,10]. We used other distinct facial expressions (e.g. [18]), as well as some variations of one expression like "low-intensity-joy" and "high-intensity-joy". The neutral expression is also included (see [11]).

Fig. 4. An example of facial expression used in the evaluation study

4.2 Procedure

In our evaluation study we asked participants to rate the degree of similarity between different facial expressions. For this purpose we ascribed the images, prepared according the procedure presented in the previous section, to ten sets. Each set s_l, l = 1,...,10, is composed of one *reference expression* and six facial expressions that have to be *compared* with the reference one. It means that each experiment session consists of 60 operations of comparison (i.e. ten sets of six comparison pairs each). To have access to a greater number of participants, we set up our experiment on the web.

One experiment session consists in passing through 10 different web pages. Each of them presents one set of images s_l (i.e. seven facial expressions). The reference image is signalled by a yellow border and it is placed in the first row. The next two rows contain expressions to be compared with the reference one. After deciding the similarity degrees for all six pairs, subjects can pass to another set. They cannot come back to the preceding sets (i.e. s_1 - s_{l-1}) and they cannot jump to the next set s_{l+1} without providing answers to the current one.

The single images as well as sets of images s_l were displayed in a random order. Images were not labelled. The participation in the experiment was anonymous. For each pair of images (i.e. reference object, compared object) subjects had to choose the degree of similarity by using a set of predefined expressions defined in natural language (five-point Likert scale, ranging from “not similar” to “equal”). In the experiment we decided to avoid the use of numerical description of the level of similarity as it is not used by people to refer to similarity.

Sixty persons participated in the experiment, but only 46 of them went through all ten sets of images. We focused only on complete responses. Twenty three participants from the 46 classified were women, the other 18 - men. The remaining 5 persons did not specify their gender.

4.3 Results

The total number of answers was 2760. First of all, we found that different labels were used by subjects with different frequency. The first label: “1 - Not at all” that corresponds to the lowest degree of similarity occurred in nearly half of all answers (46%). Other labels occurred from 10% to 16% of all responses.

In order to interpret the subjects’ answers we compared them with the values returned by our algorithm. For this purpose we changed the responses given by the subjects into numeric values. Then, we compared them with the values of fuzzy similarity. We translated a discrete set of answers given by participants to one value in the interval [0,1]. We assumed that labels are evenly placed along this interval and for each degree of similarity we associated a weight. More formally, for the purpose of measuring the answers of participants we introduced the *average similarity index*. Let *(A, B)* be a pair of expressions in which A is the reference and B is the compared object. Then u_i is the number of answers using a given label, i.e. u_1 corresponds to the label “1 – Not at all” and u_5 to the “5 – Equal”. The average similarity index, y_{AB}, is:

$$y_{AB} = \frac{\sum_{i}^{5}(w_i u_i) - w_1 \sum_{i}^{5} u_i}{(w_5 - w_1)\sum_{i}^{5} u_i} \tag{6}$$

where $w_i = i$ is the weight that corresponds to u_i. Let us notice that the values of y_{AB} and the values of fuzzy similarity *FS* (see section 3) are in the interval [0,1]. Let the vector [a_i] contains the values of our fuzzy similarity *FS* such that: a_i=FS(A_i, B_i) and let the vector [b_i] be such that: $b_i = y_{A_i B_i}$. First of all, we measured the correlation between [a_i] and [b_i]. The overall value of correlation (r) is 0.89. The *average similarity index*, y_{AB} (i.e. subjects' answers) is more or less proportional to the fuzzy similarity values (see Figure 5). The higher the index value is, the higher the fuzzy similarity value is as well. On the other hand, certain pairs were evaluated significantly higher by the participants than by the fuzzy similarity. For this reason we measured also the discrepancy between values b_i and a_i. The mean difference between b_i and a_i:

$$\frac{\sum_{i}^{n}(b_i - a_i)}{n} \tag{7}$$

is 0.09. At the same time the standard deviation of the difference [a_i] and [b_i] is 0.15. Finally, the average value of y_{AB} is 0.35.

4.4 Discussion

The aim of our experiment was to verify if the degrees of the similarity of computer generated facial expressions established by our algorithm are consistent with human perception of this phenomenon. Firstly, we compared the weighted average of the subjects' answers with the values of our algorithm. We found that the human's answers and our algorithm results are positively correlated and that the correlation coefficient is high (0.89). Also other results show that the human perception of the resemblance of facial expressions is modelled correctly by our algorithm. The average similarity index for 80% of the considered pairs is different from the perfect value (represented by the main diagonal) by 0.2 at most. Moreover, the mean difference between subjects' responses and our algorithm results is relatively small (i.e. 0.09). It is less than half of the distance between any two neighbouring degrees of similarity on the scale used by subjects in this experiment. Thus, we can say that the values of fuzzy similarity tend to be proportional to the subjects' answers. The coarse-grained scale of similarity used in this experiment probably influenced this result negatively. Subjects had to choose from a discrete set of labels, as a consequence their answers can only approximate the values of *FS*. The result is also influenced by the choice of the method of ranking the subjects' answers (i.e. y_{AB}). In particular, we assumed arbitrally that the distance between any two degrees of similarity was constant.

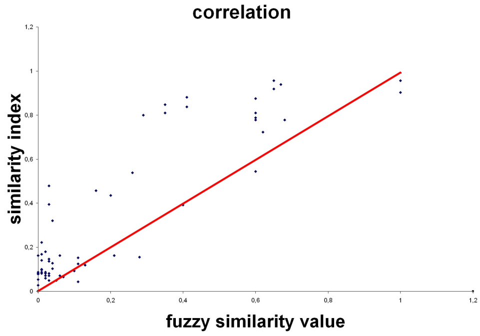

Fig. 5. Correlation between the fuzzy similarity and the average similarity index

On the other hand, the mean difference between subjects' responses and our algorithm results is positive. It means that the algorithm has a tendency to evaluate certain pairs of expressions as less similar in comparison with the subjects' choices. Indeed, we noticed certain pairs that have the fuzzy similarity value in the interval [0.3,0.5] were evaluated as relatively more similar than our algorithm indicates. Indeed, as shown in Figure 5 more points in this interval are situated above the diagonal than under it.

5 Application

In the previous section we have presented an innovative algorithm, which allowed us to compare any two facial expressions of an embodied agent. In this section we present an example of its application. We use it to generate different types of facial expressions (e.g. expressions of masking or fake expressions). Previous models [1,26] of facial expressions deal with the display of emotional states. They are based on the assumption that emotions which are similar (for instance in terms of valence or arousal values) have also similar expressions. On the contrary, we propose that the visual resemblance between two facial expressions is the measure that can be used in order to generate a new expression. We used our fuzzy similarity based algorithm in order to generate different types of facial expressions.

There is a large amount of evidence in psychological research that human's repertoire of facial expressions is very large [9,15,22]. Facial expressions do not always correspond to felt emotions but they can be fake (showing an expression of an unfelt emotion), masked (masking a felt emotion by an unfelt emotion), superposed (showing a mixed of felt emotions), inhibited (masking the expression of emotion with the neutral expression), suppressed (de-intensifying the expression of an emotion), or exaggerated (intensifying the expression of an emotion) (see [20] for detailed discussion). We called *complex facial expressions* expressions that are combinations of several facial displays. It was shown that humans can distinguish the expression of felt emotion from the expression of fake emotion or from a masked one [9,12,14,22]. In fake expressions some elements of the

original expression are missing [10], while certain elements of expression of the felt emotion can be still visible even if that expression is masked or inhibited [8]. We proposed [4] a model to generate complex facial expressions (e.g. fake expression of anger or expression of sadness masked by joy) on the basis of simple expressions (e.g. sadness, joy). This model of complex facial expressions is based on Ekman's results [7,10].

We model complex facial expressions using a face partitioning approach. The face is divided in eight facial areas F_i, i= 1,..,8 (i.e., F_1 - brows, F_2 - upper eyelids, F_3 - eyes, F_4 - lower eyelids, F_5 - cheeks, F_6 - nose, F_7 - lips movement, F_8 - lips tension, see Figure 6). Each facial expression is a composition of these facial areas, each of which can display signs of emotion. For complex facial expressions, different emotions (as in an expression masked another one) can be expressed on different areas of the face (in the example of sadness masked by anger, anger is shown on the eyebrows area while sadness is displayed on the mouth area). In our model complex facial expressions, involving one or more emotions, are composed of the facial areas of the input expressions using a set of rules. Our model can be used to generate different displays for the facial expressions of masking, as well as fake and inhibited expressions. These complex facial expressions involving the six emotions (anger, disgust, fear, joy, sadness, and surprise) are described in the literature [7,10]. For each type of expression we have defined a set of fuzzy rules that describes its characteristic features in terms of facial areas. To each emotion corresponds a rule. Thus we have defined six rules for each type of complex facial expression. In case an input expression for which the deceptive facial expression is not defined explicitly by our rules (e.g. expressions of contempt or disappointment) our fuzzy similarity based algorithm presented in the previous sections is used in order to establish the degree of similarity between the input expression and the expressions whose complex facial expressions are described by our rules. Once the most similar expression (chosen among the 6 ones) is known, we can apply the corresponding rules to our input expression. For example, when we want to compute the complex facial expression of contempt or of disappointment, we look to which expression of the six-elements set mentioned above it is the most similar to and we use the associated rule. Thus masked,

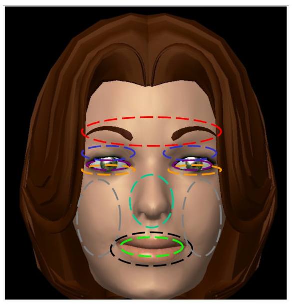

Fig. 6. The partition of the face

inhibited or fake facial expressions of two *similar* facial expressions are created using the same rules.

Figure 7b presents the agent displaying the expression of disappointment masked by a fake happiness. Our rules describe the expression of masked sadness but they do not define masked disappointment. We applied algorithm fuzzy similarity and found that disappointment has a facial expression very similar to sadness. According to Ekman [10,7] the features of felt sadness that leak over the masking expression are: forehead, brows, and upper eyelids. In our model these elements of expression are represented by the facial areas F_1(forehead and brows) and F_2 (upper eyelids). As a consequence, they can be observed in masked sadness. On the other hand, the expression of disappointment (Figure 7a) is very similar (according to the algorithm described in section 3) to the expression of sadness and so the rules of sadness will be applied also in the case of disappointment expression. Indeed in the expression of disappointment masked by fake joy (Figure 7b) we can notice the movement of brows, which is characteristic of disappointment. On the other hand the mouth area displays a smile (sign of happiness).

a b

Fig. 7. Examples of expressions: a) disappointment and b) disappointment masked by a happiness

6 Conclusion

In this paper we have presented how fuzzy similarity can be used to compare facial expressions of an embodied agent. In our approach any facial expression is described by a set of fuzzy sets. Using our algorithm we are able to compare expressions i.e. the vague and imprecise objects described by certain labels. The main advantage of this approach is that slightly different facial displays can be described by one significant label. Then using fuzzy similarity we compare these imprecise definitions and establish the degrees of similarity between them. We are unaware of any other applications of the fuzzy similarity for the purpose of comparing facial expressions.

We have also conducted a test to measure the perception of similarity between facial expressions. We checked if the perception of similarity between computer generated facial expressions is consistent with the values that are obtained with

our algorithm. The results of the test showed that the algorithm based on the fuzzy similarity meets our expectations. Finally we have also presented an application of our algorithm for generating facial expressions.

It is important to stress that in a more realistic model of similarity one should take into consideration also the probability of occurrence of certain values for a FAP. It means that even if a fuzzy set defines plausible values for a certain expression it does not mean that all these values occur with the same frequency. The similarity between two objects has to take into account the probability of occurrence of the values from the given interval (see [24]) to avoid for instance that two attributes "become similar" because of similar values but that occur very seldom. Unfortunately, we do not have the data of this type for facial expressions. In this situation we assumed that all values are equi-probable.

In the future, we aim to create fuzzy definitions of facial expressions based on empirical data. Consequently, the shapes of the fuzzy sets that describe the features of facial expression will be uniquely defined for each expression (see [26]). All parts of the face are considered as equi-important in our similarity algorithm at current stage of development. However, it is known that each face areas of the face can have a different role in the perception of emotion ([3,6]). We want to test if it is also the case for the perception of similarity.

Acknowledgement. We are very grateful to Giulianella Coletti and to Andrea Capotorti for their help on fuzzy methods. We also thank Elisabetta Bevacqua and Maurizio Mancini for implementing the Greta system. Part of this research is supported by the EU FP6 Network of Excellence HUMAINE (IST-2002-2.3.1.6) and by the EU FP6 Integrated Project Callas (FP6-2005-IST-5).

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